





Performance Scalability of a Remote Sensing Application on High Performance Reconfigurable Platforms

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Outline

- Objective
- Motivations
- Cloud Detection and Landsat 7 ACCA
- Implementation Approach
- Experimental Results
- Concluding Remarks

Objective

 Proof of concept for an onboard system for cloud detection using High Performance Reconfigurable Computers (HPRCs)

- ◆ Targets Landsat 7 ETM+ and ACCA algorithm to:
 - Operation of the potential performance of HPRCs
 - O Gain an insight into the system level programmability and performance issues

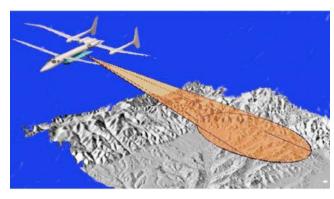
Motivations

El-Araby, GWU

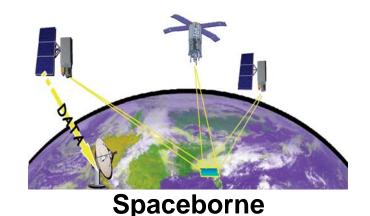
- Why Cloud Detection?
 - Ocan render data useless in landuse/land cover studies
 - Oritical in weather and climate studies



- 0 Reduction of communication bandwidth
- 0 Reduce cost and complexity of ground processing systems
- 0 Enable autonomous decisions
- Why Reconfigurable?
 - Flexibility is Important for Space
 - O High Performance, ...



Airborne



Outline

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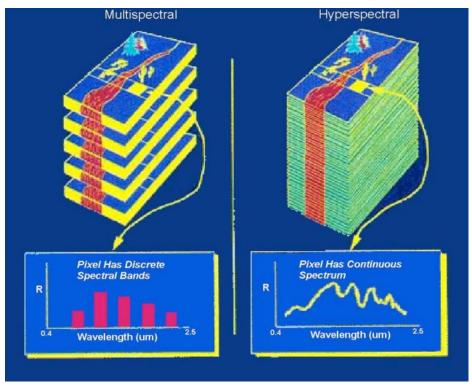
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Remote Sensing

Multi-Spectral Imagery

Hyperspectral Imagery

0 100's-1000's of bands (AVIRIS \equiv 224 bands, AIRS \equiv 2378 bands)

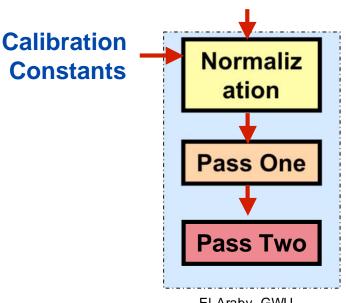


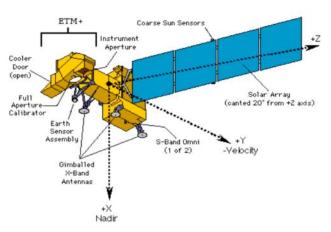
Multispectral / Hyperspectral Imagery Comparison

Landsat 7 AND Cloud Detection

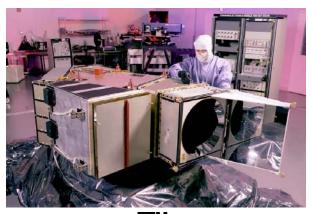
- ACCA (Automatic Cloud Cover Assessment) for Landsat 7 ETM+
 - 0 ETM+ has 8 bands
 - O ACCA algorithm uses Band2- Band6
 - O Threshold based 8 filters (tests)
 - O Three-Step approach







Landsat 7



ETM+

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Cloud Detection Theory

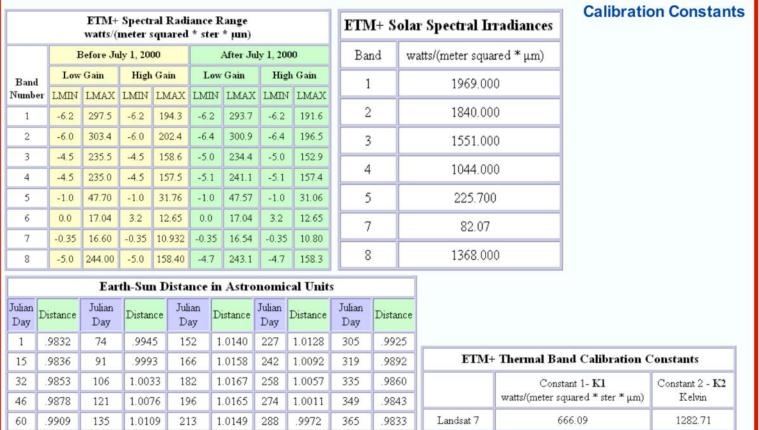
- Idea is based on the observation that clouds are Highly Reflective and Cold:
 - 0 Highly reflective (in the visible, near- and mid- IR bands)
 - Visible Bands
 - » Green band (Band2 \equiv 0.52 0.60 μ m)
 - ◆ Measures green reflectance → Vegetation discrimination
 - » Red band (Band3 \equiv 0.63 0.69 μ m)
 - ◆ Measures Chlorophyll absorption → Plant Species differentiation
 - Combined with Green Band shows land surface as red-like

Cloud Detection Theory (cnt'd)

- Near-IR Band (Band4 ≡ 0.76 0.90 μm)
 - ◆ Determines soil moisture level → Delineating water bodies and distinguishing vegetation types
- \bullet Mid-IR Band (Band5 ≡ 1.55 1.75 µm)
 - Differentiation of snow from clouds
- 0 Cold (in the thermal bands)
 - ◆Thermal IR Band (Band6 ≡ 10.4 12.5 μm)
 - Thermal mapping to Brightness Temperatures
 - Difference between 11 μm & 12 μm highlights cloud boundaries

(Algorithm Outline)

- Normalization
 - O Bands 2-5 (Reflectance bands)
 - O Band 6 (Thermal band)
 - Calibrated to blackbody Brightness Temperature



Normalization

Pass One

Pass Two

(Algorithm Outline)

Normalization

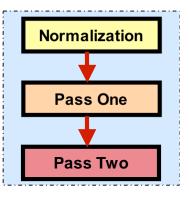
- 0 Extract the calibration constants ($L_{MIN\lambda}$, $L_{MAX\lambda}$, d, $E_{SUN\lambda}$, θ_s , K_1 , K_2) from the tables depending on the information in the data file headers
- 0 Calculate radiance (L_{λ}) for captured data
- Calculate reflectance (ρ) for band 2-5
- O Calculate temperature (7) for band 6 only
- Reflectance is a linear function of the raw quantized data (Q_{cal})
- Temperature is a non-linear function of the raw data

$$\begin{split} L_{\lambda_i} &= \left(\frac{L_{\max_{\lambda_i}} - L_{\min_{\lambda_i}}}{Q_{cal_{\max}} - Q_{cal_{\min}}}\right) \left(Q_{cal_i} - Q_{cal_{\min}}\right) + L_{\min_{\lambda_i}} \\ \forall \ i \in \left\{2,3,4,5,6\right\} \\ \rho_{p_i} &= \frac{\pi \cdot d^2}{E_{sun_{\lambda_i}} \cos(\theta_s)} \cdot L_{\lambda_i} \ , \ \forall \ i \in \left\{2,3,4,5\right\} \\ \rho_{p_i} &= \beta_i \cdot Q_{cal_i} + \alpha_i \ , \ \forall \ i \in \left\{2,3,4,5\right\} \\ T &= \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda_i}} + 1\right)} \ , \ i = 6 \end{split}$$

(Algorithm Outline)

- ◆ Pass One
 - 0 Identifies clouds (produces Cloud Mask)
 - Minimizes errors of commission

	Filter Function	
1	Brightness Threshold $B_3 > 0.08$	Eliminates dark images
2	Normalized Difference Snow Index (NDSI) $NDSI = \frac{B_2 - B_5}{B_2 + B_5} < 0.7$	Eliminates many types of snow
3	Temperature Threshold $B_6 < 300 K$	Eliminates warm image features
4	Band 5/6 Composite $(1 - B_5)B_6 < 225$	Eliminates numerous categories including ice
5	Band 4/3 ratio $\frac{B_4}{B_3} < 2$	Eliminates bright vegetation and soil
6	Band 4/2 ratio $\frac{B_4}{B_2} < 2$	Eliminates ambiguous features
7	Band 4/5 ratio $\frac{B_4}{B_5} > 1$	Eliminates rocks and desert
8	Band 5/6 Composite $(1 - B_5)B_6 > 210 \implies warm clouds$ $(1 - B_5)B_6 < 210 \implies cold clouds$	Distinguishes warm clouds from cold clouds



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(Algorithm Outline)

Classification	Rule	
Snow	$\left(NSDI = \frac{B_2 - B_5}{B_2 + B_5} > 0.7\right) AND \left(B_4 > 0.1\right)^A$	
Desert	$\frac{B_4}{B_5} < 0.83^B$	
NotCloud	$\left(B_3 < 0.08\right) \ OR \ \left(B_6 > 300\right) \ OR \ \left(Snow\right)$	
Ambiguous $\left(((1-B_5)B_6 > 225) \ OR\left(\frac{B_4}{B_3} > 2\right) \ OR\left(\frac{B_4}{B_2} > 2\right) \ OR\left(Desert\right) \ AND \ (\sim NotCloub) \right)$		
ColdCloud	$((1-B_5)B_6 \ge 210)$ AND $(\sim Ambiguous)$ AND $(\sim NotCloud)$	
WarmCloud	$((1-B_5)B_6 < 210)$ AND $(\sim Ambiguous)$ AND $(\sim NotCloud)$	

Classification Rules for Pass One [2]

(Algorithm Outline)

Pass Two

- O Defines ambiguous clouds
 - Thermal properties of clouds identified during Pass One are characterized and used to identify remaining cloud pixels
 - Band 6 statistical moments (mean, standard deviation, skew, kurtosis)
 are computed for clouds identified during Pass One
 - The 95th percentile becomes the new thermal threshold for Pass Two
 - Image pixels that fall below the new thermal threshold and survive the first three Pass-One filters are classified as clouds

$$\eta = \frac{1}{n} \sum_{i=1}^{n} x_i , \sigma^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \eta)^2$$

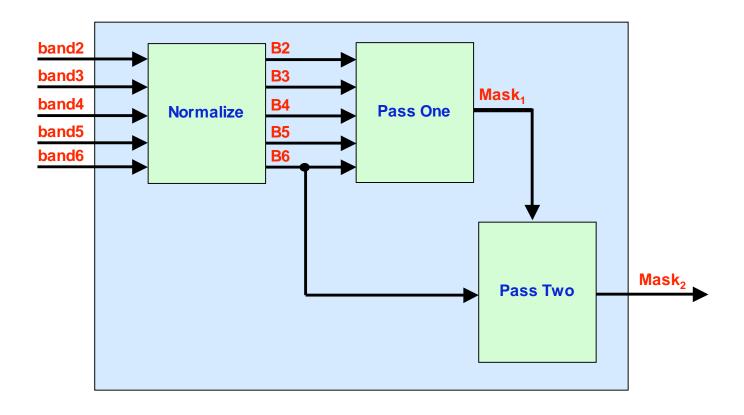
$$Skewness = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \eta}{\sigma}\right)^3$$

$$Kurtosis = \frac{1}{n-3} \sum_{i=1}^{n} \left(\frac{x_i - \eta}{\sigma}\right)^4$$

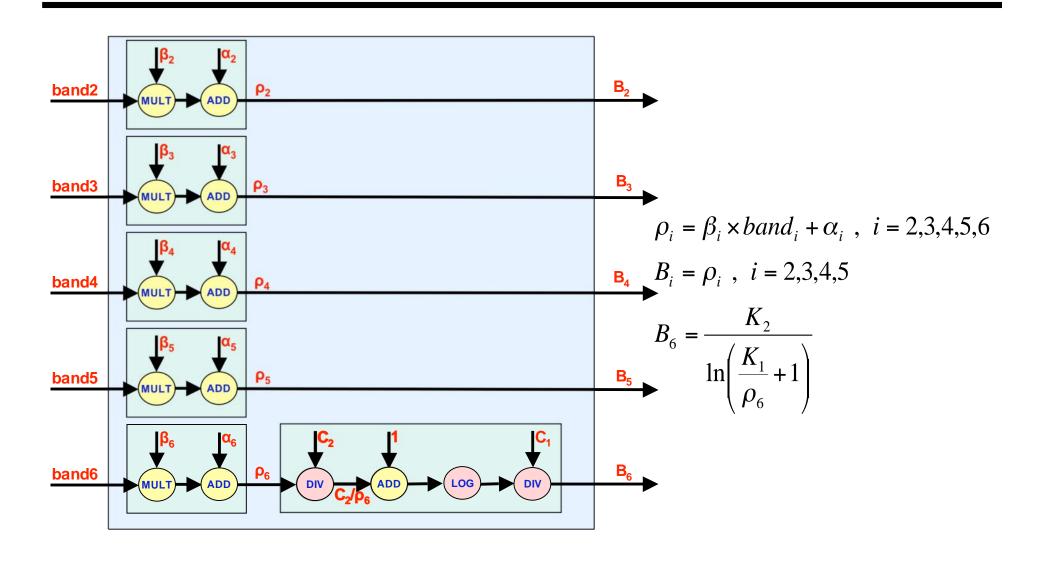
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 - **O Architectural Modules**
 - 0 Testbed (SRC-6 and Cray-XD1)
- **♦** Experimental Results
- Concluding Remarks

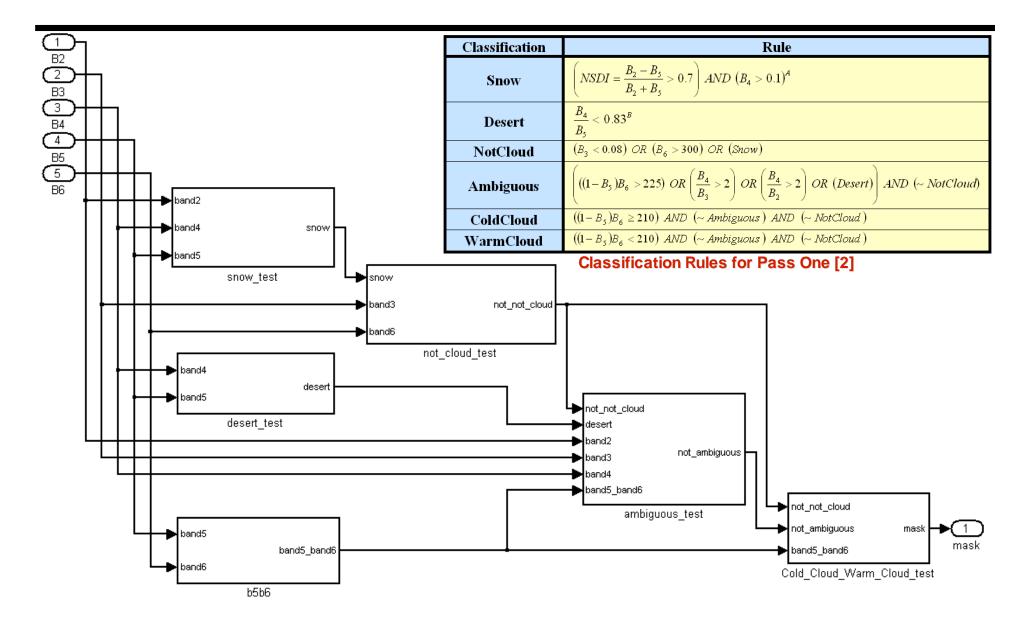
Top Hierarchy Module



Normalization Module

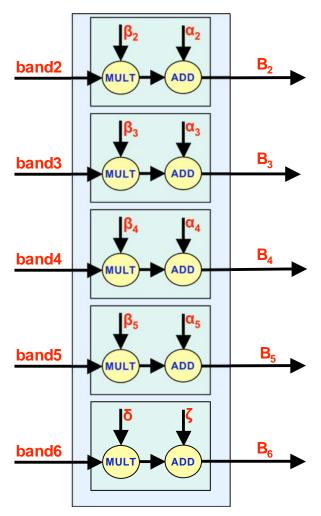


Pass-One Module



Optimizing Hardware Resources Usage

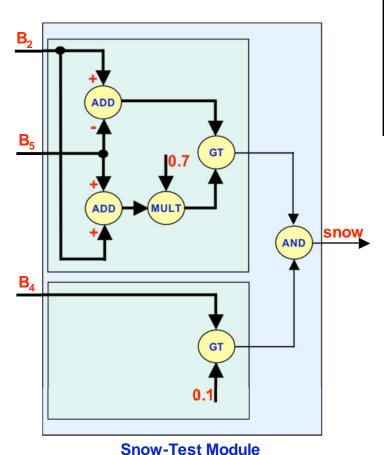
(Linearization of the Normalization Function)



$$\begin{array}{l} \mathbf{B_{2}} \\ \bullet \\ B_{i} = \beta_{i} \times band_{i} + \alpha_{i} , i = 2,3,4,5,6 \\ B_{i} = \rho_{i} , i = 2,3,4,5 \\ \\ B_{6} = \frac{K_{2}}{\ln\left(\frac{K_{1}}{\rho_{6}} + 1\right)} \cong \frac{K_{2}}{1 + \ln(K_{1})} + \frac{K_{2}\left(1 - \frac{1}{K_{1}}\right)}{\left(1 + \ln(K_{1})\right)^{2}} \times \rho_{6} \\ \\ \mathbf{B_{5}} \\ \bullet \\ B_{6} \cong \left(\frac{K_{2}}{1 + \ln(K_{1})} + \frac{K_{2}\left(1 - \frac{1}{K_{1}}\right) \cdot \alpha_{6}}{\left(1 + \ln(K_{1})\right)^{2}}\right) + \left(\frac{K_{2}\left(1 - \frac{1}{K_{1}}\right) \cdot \beta_{6}}{\left(1 + \ln(K_{1})\right)^{2}}\right) \times band_{6} \\ \\ B_{6} \cong \zeta + \delta \times band_{6} \end{array}$$

Optimizing Hardware Resources Usage (cnt'd)

(Algebraic Re-Formulation of Pass-One Filters)



Classification	Rule	
Snow $\left(NSDI = \frac{B_2 - B_5}{B_2 + B_5} > 0.7\right) AND \left(B_4 > 0.1\right)^A$		
Desert $\frac{B_4}{B_5} < 0.83^B$		
NotCloud	$\left(B_3 < 0.08\right) \ OR \ \left(B_6 > 300\right) \ OR \ \left(Snow\right)$	
Ambiguous $ \left(((1-B_5)B_6 > 225) \ OR \left(\frac{B_4}{B_3} > 2 \right) \ OR \left(\frac{B_4}{B_2} > 2 \right) \ OR \ (Desert) \right) \ AND \ (\sim No.) $		
ColdCloud	ColdCloud $((1-B_5)B_6 \ge 210)$ AND $(\sim Ambiguous)$ AND $(\sim NotCloud)$	
WarmCloud $((1-B_5)B_6 < 210)$ AND $(\sim Ambiguous)$ AND $(\sim NotCloud)$		

Classification Rules for Pass One [2]

Division Eliminated



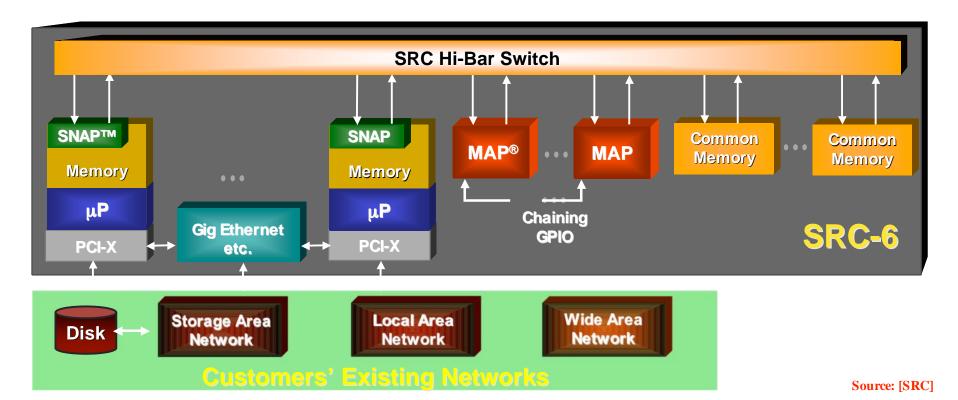
20

Outline

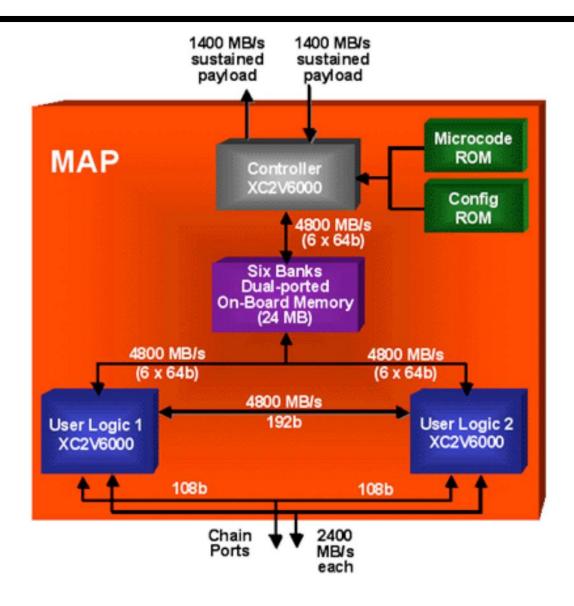
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SRC Hi-Bar[™] Based Systems

- Hi-Bar sustains 1.4 GB/s per port with 180 ns latency per tier
- Up to 256 input and 256 output ports with two tiers of switch
- Common Memory (CM) has controller with DMA capability
- Controller can perform other functions such as scatter/gather
- Up to 8 GB DDR SDRAM supported per CM node



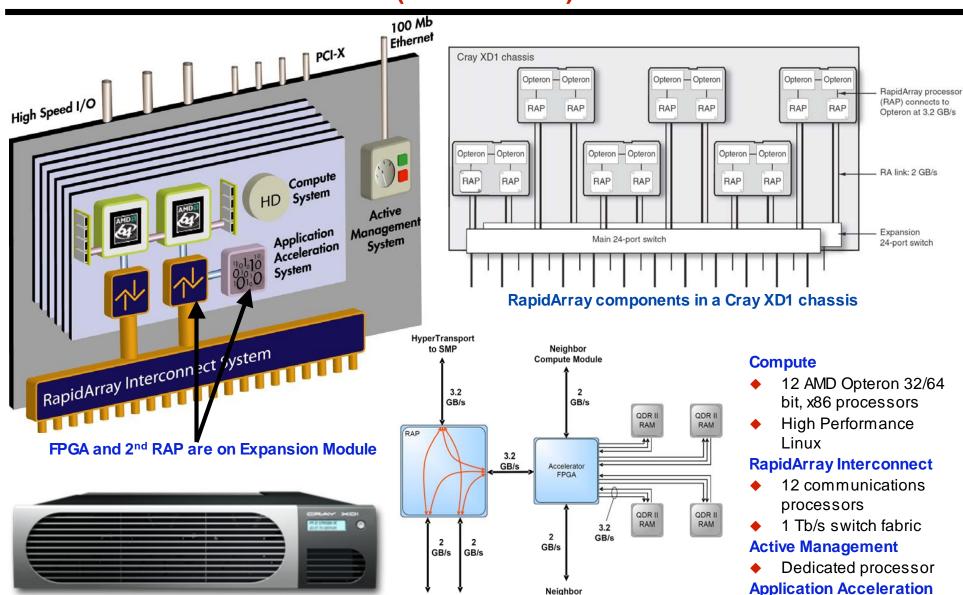
SRC Reconfigurable Processor



Source: [SRC]

Cray XD1 System Architecture

(One Chassis)



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Compute Module

RapidArray

Application Acceleration

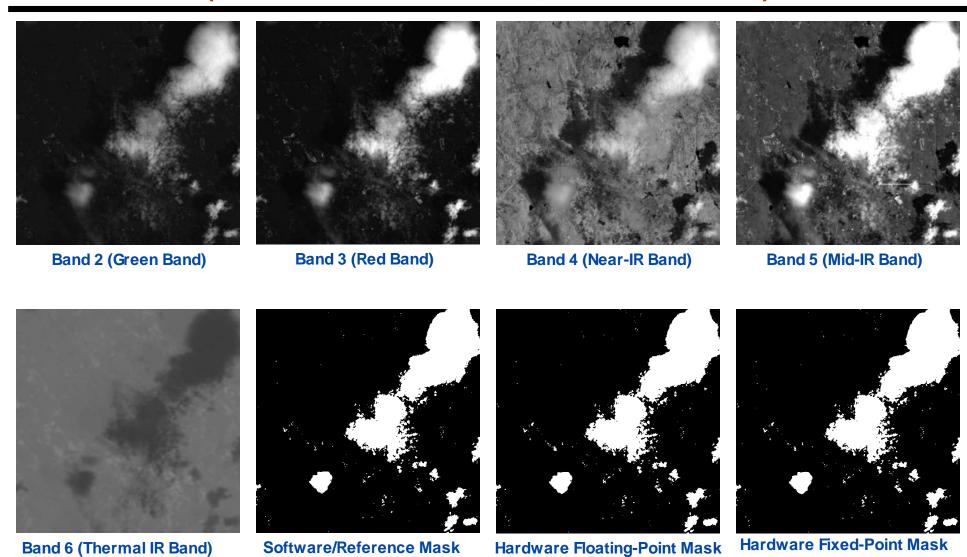
6 co-processors June 27, 2006

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 - **O Detection Accuracy**
 - **0** Measurements
 - **O** Performance
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Detection Accuracy

(Software/Reference Mask, Hardware Masks)



(Approximate Normalization)

(Approximate Normalization)

Detection Accuracy (cnt'd)

(Approximate Normalization and Quantization Errors)



Approximation Error (0.1028 %)



Hardware Fixed-Point (12-bit) Error (0.2676 %)



Hardware Floating-Point Error (0.1028 %)



Hardware Fixed-Point (23-bit) Error (0.1028 %)

$$error = \frac{\sum_{i=0}^{(rows-1)} \sum_{j=0}^{(columns-1)} \left(x_{ij} - y_{ij}\right)}{rows \times columns}$$

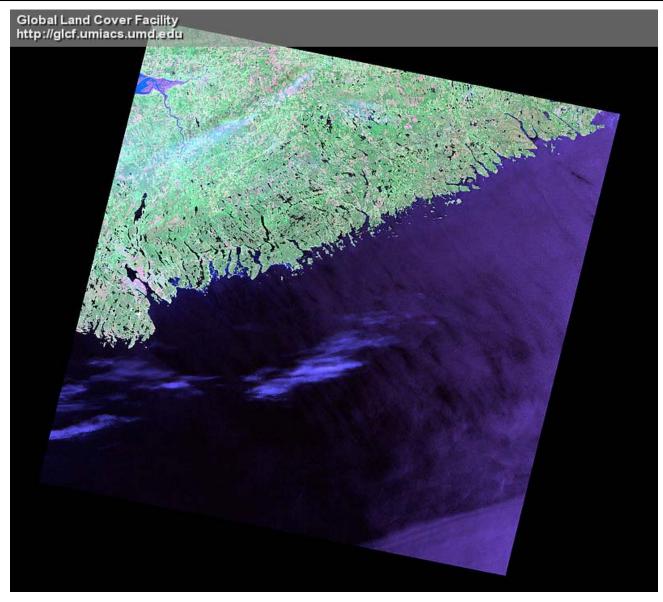
where

x = output image,

y = reference image

Reported Error (1.02 %) by Williams et al. [2]

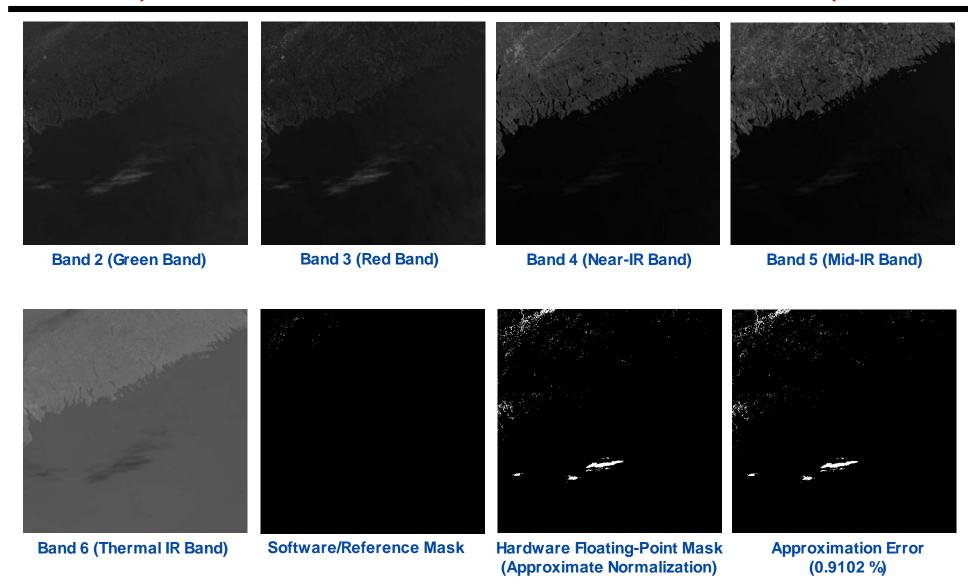
Detection Accuracy over Water



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Detection Accuracy over Water

(Software/Reference Mask, Hardware Mask, Error Mask)



ACCA Resource Utilization

Platform	MAP Virtex II 6000
Speed	100 MHz
Slices	4,623 (13%)
LUTs	3,865 (5%)
Slice Flip Flops	8.023 (11%)
MULT 18X18	6 (4%)
RAMB16	6 (4%)

Platform	MAP Virtex-II 6000
Speed	100 MHz
Latency	78 Stages
Slices	17,565 (51%)
LUTs	20,885 (30%)
Slice Flip Flops	23,005 (34%)
MULT 18X18	36 (25%)

VHDL Fixed-Point (23-bit) of

Pass-One

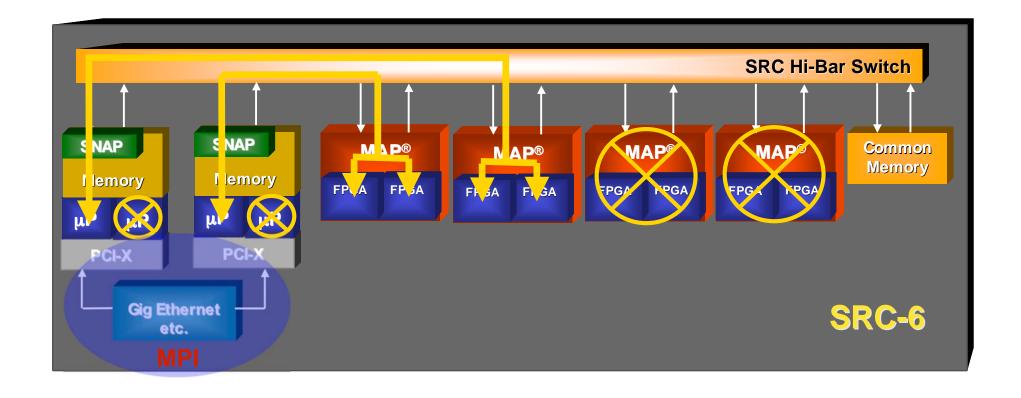
MAP-C Floating Point (Single-Precision) of Pass-One

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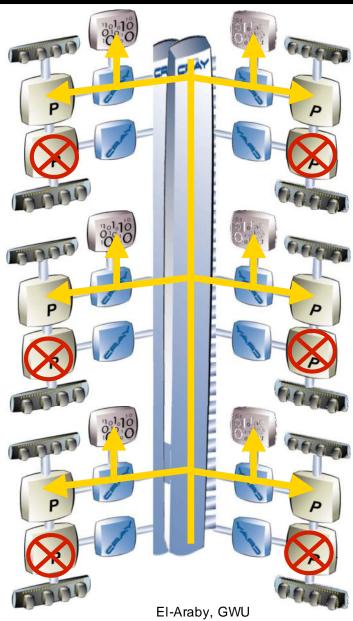
Platform	MAP Virtex-II 6000
Speed	100 MHz
Latency	1184 Stages
Slices	31,117 (92%)
LUTs	37,977 (56%)
Slice Flip Flops	40,584 (60%)
MULT 18X18	59 (40%)

MAP-C Floating Point of Pass-One & Partially Pass-Two

Multi-Node Measurements Scenarios on SRC-6



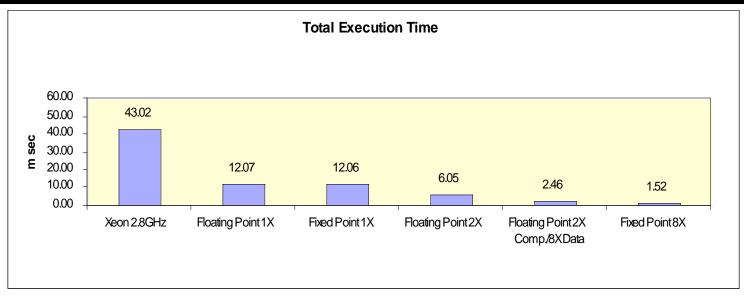
Multi-Node Measurements Scenarios on Cray-XD1

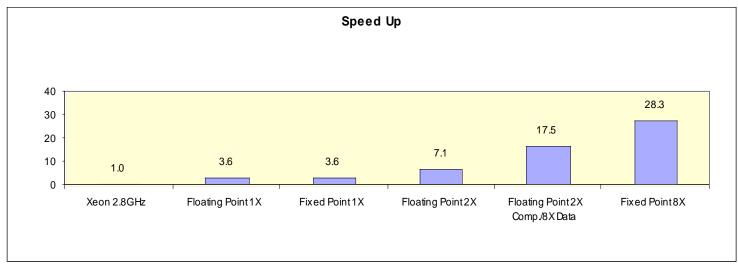


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SRC-6 vs. Intel Xeon 2.8 GHz

(Hardware-to-Software Performance)





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Multi-Node Execution Time

ACCA on SRC-6

Number of	Processing Time (msec)		Communication
FPGAs	1 Engine/Chip	8 Engines/Chip	Overhead (msec)
1	12.07	1.52	0
2	6.035	0.76	4.01
4	3.0175	0.38	4.2

ACCA on Cray-XD1

Number of	Processing Time (msec)		Communication
Nodes	1 Engine/Chip	8 Engines/Chip	Overhead (msec)
1	3.16	0.39	0
2	1.49	0.19	3.9
4	1.01	0.13	4.5
5	0.75	0.09	4.49
6	0.67	0.08	4.58

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Concluding Remarks

- We extended our previous effort [3] by:
 - Investigating the potential of using multi-node HPRCs for onboard preprocessing
- Landsat 7 ETM+ ACCA algorithm was selected to:
 - Operation of the potential performance of HPRCs
 - O Gain an insight into the system level programmability and performance issues
- We studied and characterized the scalability of the application:
 - On two of the state-of-the-art reconfigurable platforms, SRC-6 and Cray-XD1 at HPCL/GWU
- ◆ The workload was distributed over all nodes using MPI:
 - We scattered the input five bands across all nodes, and
 - O Gathered the resulting mask pixels from all nodes at the base node

Concluding Remarks (cnt'd)

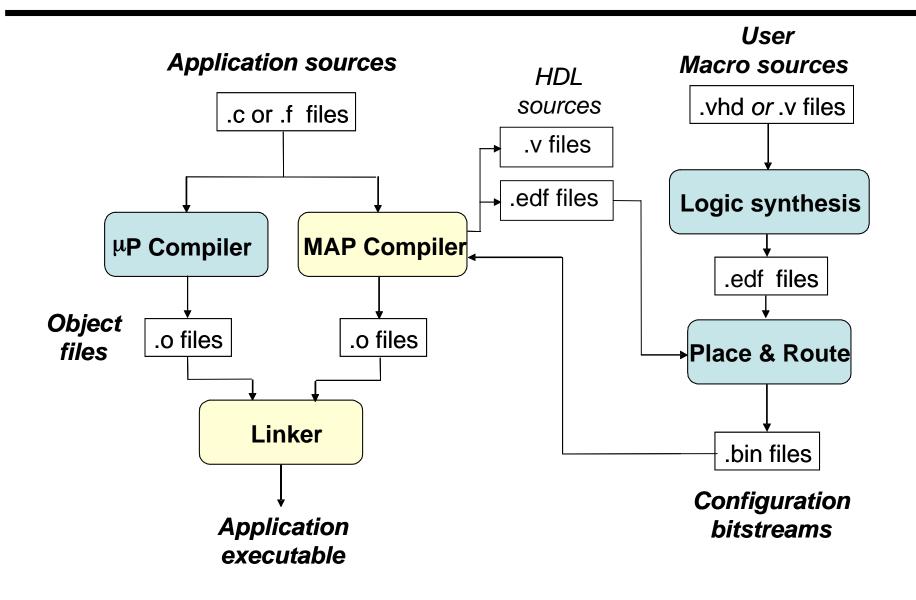
- ◆ The <u>computation scalability</u> on both machines was shown to be close to ideal
 - The communication overhead was almost constant irrespective of the number of nodes
 - The inherent parallelism of the application was fully exploited
- ◆ A deviation in the <u>overall scalability</u> from the ideal was observed and analyzed:
 - Overheads, such as communications, must be at a much lower levels than what is accepted in conventional high performance computers
- The results also showed that:
 - We may not need very large machines that are characterized with high overhead when HPRCs are used, which is a requirement for on-board preprocessing

References

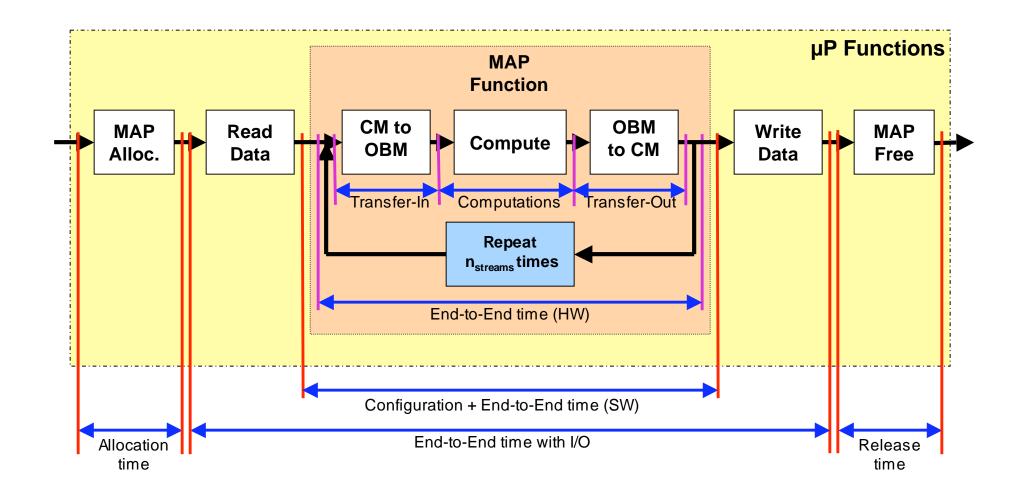
- [1] A. Michalski, K. Gaj, D.A. Buell, "High-Throughput Reconfigurable Computing: A Design Study of an IDEA Encryption Cryptosystem on the SRC-6e Reconfigurable Computer", FPL 2005, pp.681-686.
- [2] J.A. Williams, A.S. Dawood, S.J. Visser, "FPGA-based Cloud Detection for Real-Time Onboard Remote Sensing," Proceedings of IEEE International Conference on Field-Programmable Technology (FPT 2002), 16-18 Dec. 2002, pp.110 116.
- [3] E. El-Araby, M. Taher, T. El-Ghazawi, and J. Le Moigne, "Prototyping Automatic Cloud Cover Assessment (ACCA) Algorithm for Remote Sensing On-Board Processing on a Reconfigurable Computer", IEEE International Conference on Field-Programmable Technology (FPT 2005), Singapore, 11-14 Dec., 2005.
- [4] E. El-Araby, T. El-Ghazawi, J. Le Moigne, and K. Gaj, "Wavelet Spectral Dimension Reduction of Hyperspectral Imagery on a Reconfigurable Computer," IEEE International Conference on Field-Programmable Technology, FPT 2004, Brisbane, Australia, December 2004.
- [5] "SRC-6 C-Programming Environment Guide", SRC Computers, Inc. 2005.
- [6] "S-2433-131 Cray XD1TM Programming", Cray Inc., Oct. 2005.
- [7] "S-6400-131 Cray XD1TM FPGA Development", Cray Inc., Oct. 2005.
- [8] R.R. Irish, "Landsat 7 Automatic Cloud Cover Assessment," Algorithms for Multispectral, Hyperspectral and Ultraspectral Imagery VI, SPIE, Orlando, FL., USA, 24-26 April 2000, pp.348-355.
- [9] J.A. Williams, A.S. Dawood, S.J. Visser, "Real-Time Wildfire and Volcanic Plume Detection from Spaceborne Platforms with Reconfigurable Logic," 11th Australasian Remote Sensing and Photogrammetry Conference, Brisbane, Australia, 2-6 September 2002.
- [10] R.S. Basso, J. Le Moigne, S. Veuella, and R.R. Irish, "FPGA Implementation for On-Board Cloud Detection," International Geoscience and Remote Sensing Symposium. Hawaii, 20-24 July 2000.

Backup Slides

SRC Software Environment

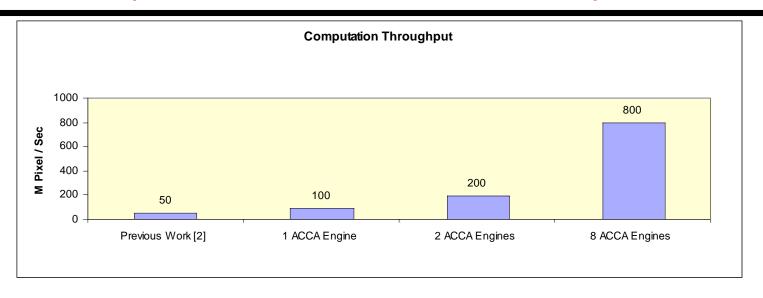


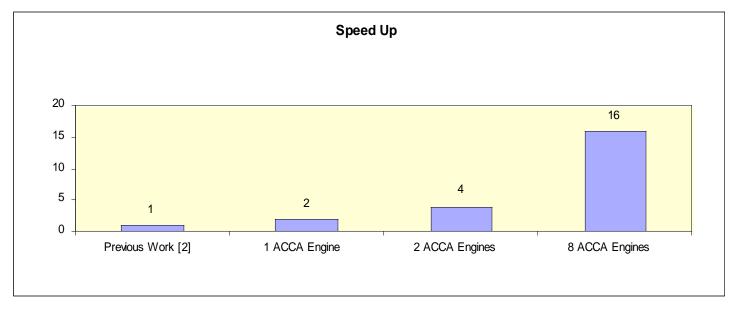
Single-Node Measurements Scenarios on SRC-6



Hardware Computation Throughput

(Hardware-to-Hardware Performance)

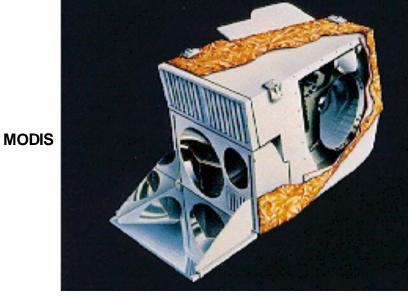


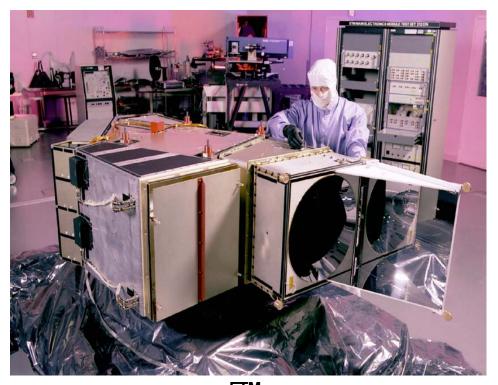


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Cloud Detection: Example Satellites and Algorithms







ETM+

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Optimizing Hardware Resources Usage

(Linearization of the Normalization Function)

$$\rho_i = \beta_i \times band_i + \alpha_i$$
, $i = 2,3,4,5,6$

$$B_i = \rho_i$$
, $i = 2,3,4,5$

$$B_{6} = \frac{K_{2}}{\ln\left(\frac{K_{1}}{\rho_{6}} + 1\right)} = \frac{K_{2}}{\ln\left(\frac{K_{1}}{\rho_{6}}\left(1 + \frac{\rho_{6}}{K_{1}}\right)\right)} = \frac{K_{2}}{\ln\left(\frac{K_{1}}{\rho_{6}}\right) + \ln\left(1 + \frac{\rho_{6}}{K_{1}}\right)} = \frac{K_{2}}{\ln(K_{1}) - \ln(\rho_{6}) + \ln\left(1 + \frac{\rho_{6}}{K_{1}}\right)}$$

when
$$|x| < 1 \implies \ln(1+x) \cong x$$
, $\frac{1}{1-x} \cong 1+x$

$$\because (0 < \rho_6 < 1) \ and \ (K_1 >> 1) \Rightarrow 0 < \frac{\rho_6}{K_1} < 1 \Rightarrow \ln\left(1 + \frac{\rho_6}{K_1}\right) \cong \frac{\rho_6}{K_1}$$

$$\therefore B_6 = \frac{K_2}{\ln(K_1) - \ln(\rho_6) + \ln(1 + \frac{\rho_6}{K_1})} = \frac{K_2}{\ln(K_1) - \ln(1 + (\rho_6 - 1)) + \ln(1 + \frac{\rho_6}{K_1})} \cong \frac{K_2}{\ln(K_1) - (\rho_6 - 1) + \frac{\rho_6}{K_1}}$$

Optimizing Hardware Resources Usage

(Linearization of the Normalization Function)

$$B_{6} \cong \frac{K_{2}}{\ln(K_{1}) - (\rho_{6} - 1) + \frac{\rho_{6}}{K_{1}}} \cong \frac{K_{2}}{1 + \ln(K_{1}) - \rho_{6} + \frac{\rho_{6}}{K_{1}}} \cong \frac{K_{2}}{1 + \ln(K_{1}) - \rho_{6} \left(1 - \frac{1}{K_{1}}\right)} \cong \frac{K_{2}}{1 + \ln(K_{1})} \cdot \left(\frac{1}{1 - \frac{1}{K_{1}}}\right) = \frac{1}{1 + \ln(K_{1})}$$

:
$$(0 < \rho_6 < 1)$$
 and $(K_1 >> 1) \Rightarrow 0 < \rho_6 \cdot \frac{\left(1 - \frac{1}{K_1}\right)}{1 + \ln(K_1)} < 1$

$$\therefore B_{6} \cong \frac{K_{2}}{1 + \ln(K_{1})} \cdot \left(\frac{1}{1 - \frac{1}{K_{1}}}\right) = \frac{K_{2}}{1 + \ln(K_{1})} \cdot \left(1 + \rho_{6} \cdot \frac{\left(1 - \frac{1}{K_{1}}\right)}{1 + \ln(K_{1})}\right) \cong \frac{K_{2}}{1 + \ln(K_{1})} + \frac{K_{2} \cdot \left(1 - \frac{1}{K_{1}}\right)}{\left(1 + \ln(K_{1})\right)^{2}} \cdot \rho_{6}$$

Optimizing Hardware Resources Usage

(Linearization of the Normalization Function)

$$B_6 = \frac{K_2}{\ln\left(\frac{K_1}{\rho_6} + 1\right)} \cong \frac{K_2}{1 + \ln(K_1)} + \frac{K_2\left(1 - \frac{1}{K_1}\right)}{\left(1 + \ln(K_1)\right)^2} \times \rho_6$$

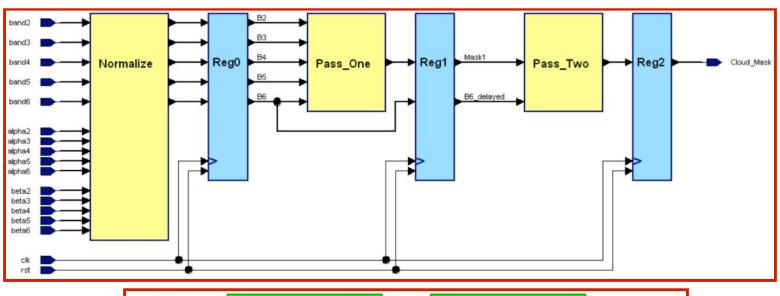
$$\therefore \rho_6 = \beta_6 \times band_6 + \alpha_6$$

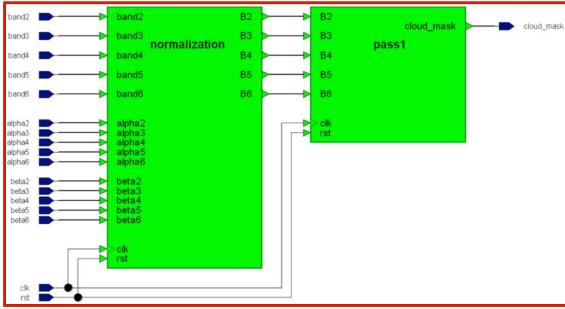
$$\therefore B_6 \cong \frac{K_2}{1 + \ln(K_1)} + \frac{K_2 \left(1 - \frac{1}{K_1}\right)}{\left(1 + \ln(K_1)\right)^2} \times \left(\beta_6 \times band_6 + \alpha_6\right)$$

$$B_{6} \cong \left(\frac{K_{2}}{1 + \ln(K_{1})} + \frac{K_{2}\left(1 - \frac{1}{K_{1}}\right) \cdot \alpha_{6}}{\left(1 + \ln(K_{1})\right)^{2}}\right) + \left(\frac{K_{2}\left(1 - \frac{1}{K_{1}}\right) \cdot \beta_{6}}{\left(1 + \ln(K_{1})\right)^{2}}\right) \times band_{6}$$

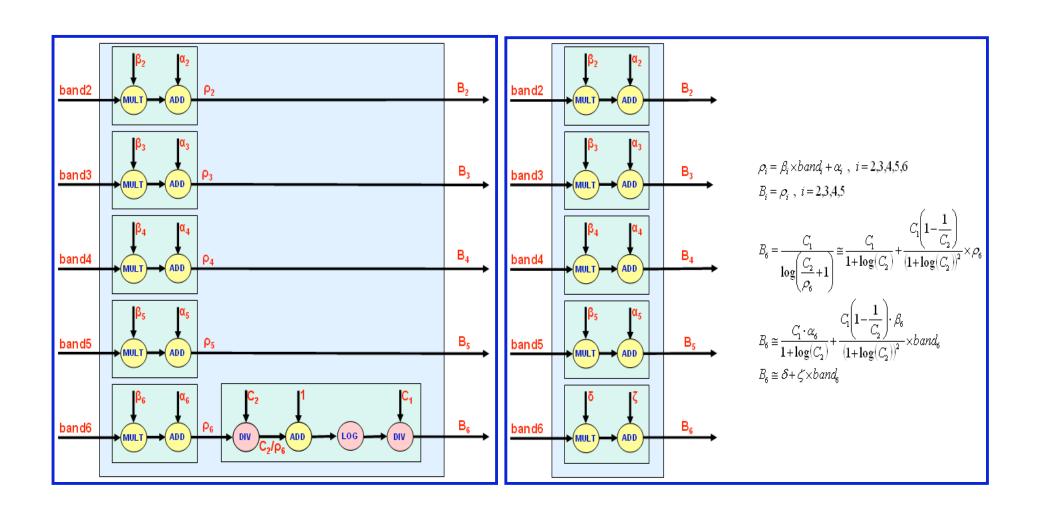
$$B_6 \cong \zeta + \delta \times band_6$$

Top-Level Architecture of the ACCA Algorithm

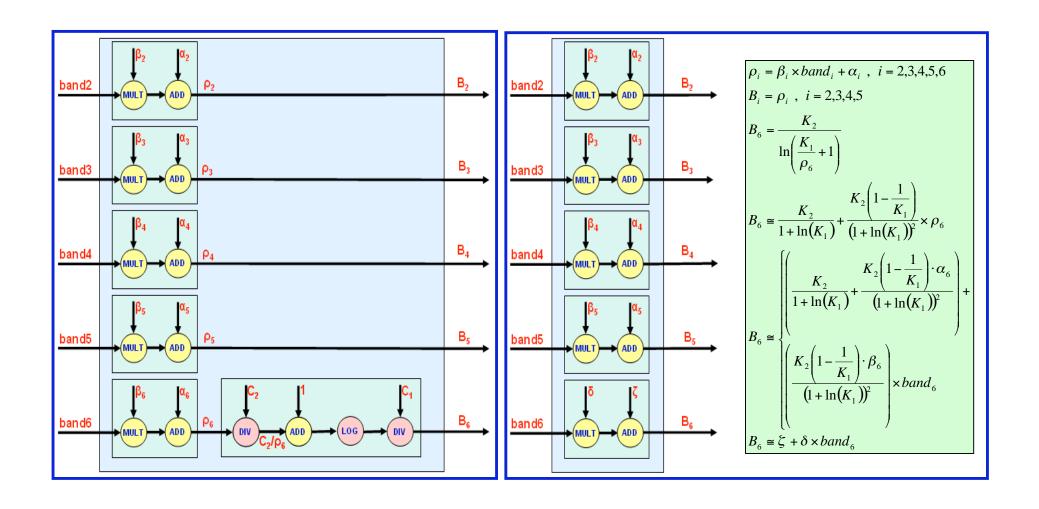




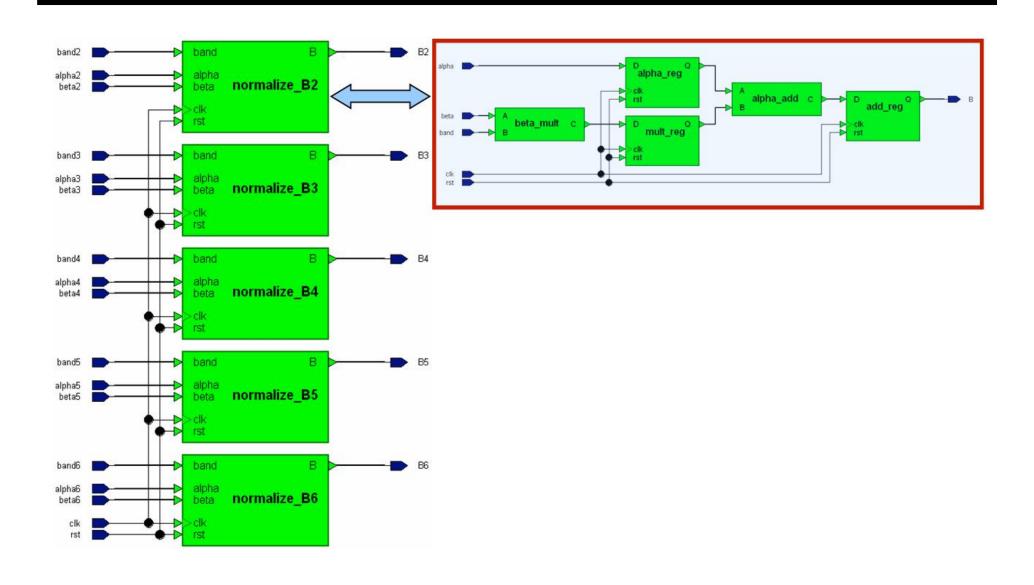
Normalization Module



Normalization Module

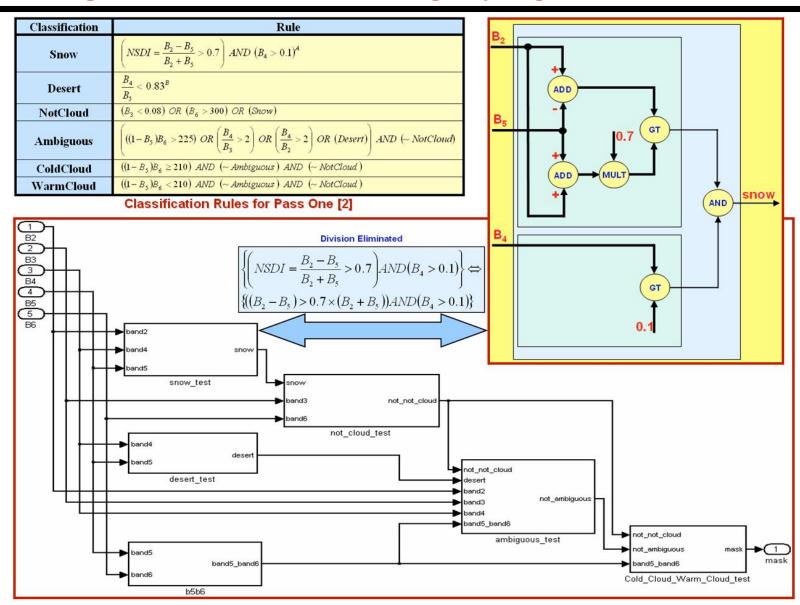


Normalization Module (cnt'd)

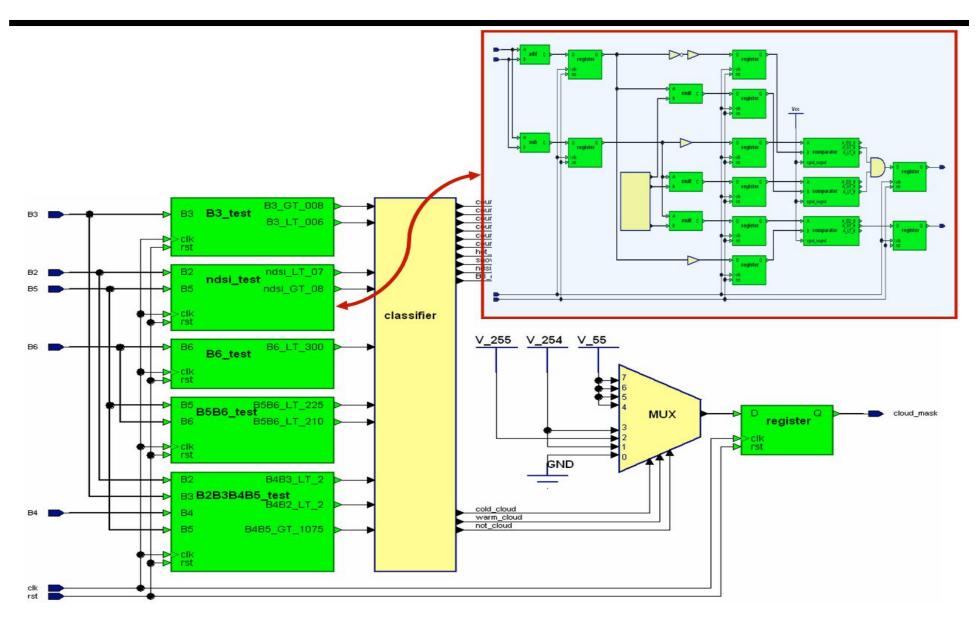


Pass-One Module

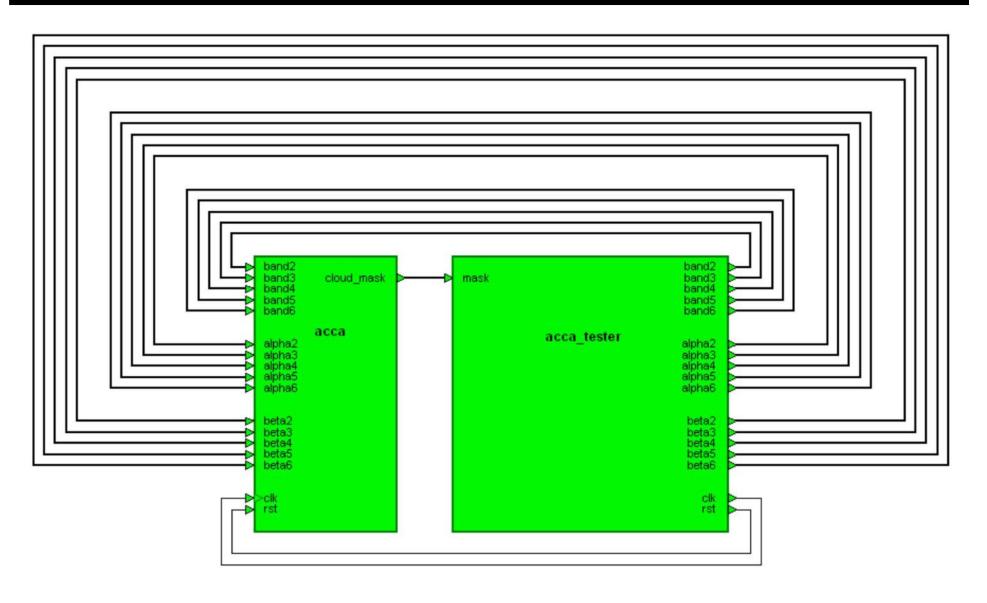
(Optimizing Hardware Resources Usage by Algebraic Re-Formulation)



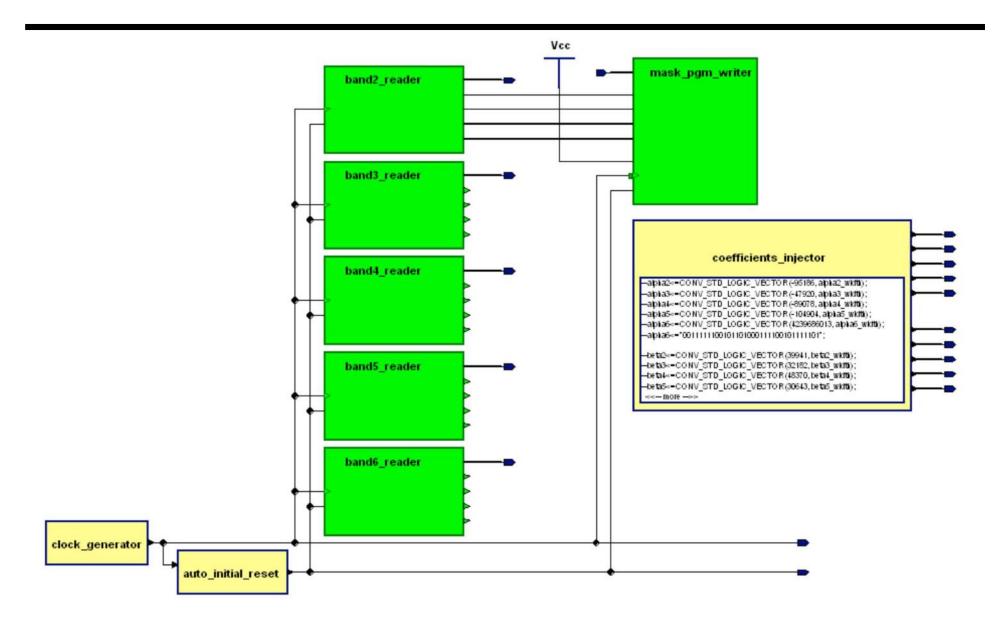
Pass-One Architecture



Test Bench



Tester Architecture



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Image Reader and Writer

